



ARL-TR-7684 • MAY 2016



Modeling the Impact of Value of Information on Situational Awareness Using C3TRACE

by John T Richardson, Mark R Mittrick, and
Timothy P Hanratty

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Computational and Information Sciences Directorate, ARL

REPORT DOCUMENTATION PAGE				Form Approved OMB No. 0704-0188	
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1. REPORT DATE (DD-MM-YYYY) May 2016		2. REPORT TYPE Final		3. DATES COVERED (From - To) 1 September 2014–30 April 2016	
4. TITLE AND SUBTITLE Modeling the Impact of Value of Information on Situational Awareness Using C3TRACE				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) John T Richardson, Mark R Mittrick, and Timothy P Hanratty				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) US Army Research Laboratory ATTN: RDRL-CII-T Aberdeen Proving Ground, MD 21005-5067				8. PERFORMING ORGANIZATION REPORT NUMBER ARL-TR-7684	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution is unlimited.					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT <p>Situational awareness (SA) is critical to making good decisions on the battlefield. For the military intelligence analyst, SA is built by the assessment of incoming reports. It is hard to tell good information from bad before assessing the reports, and in today's age of unprecedented amounts of data, it is simply impossible to assess all available reports in a time-limited military scenario. The US Army Research Laboratory (ARL) has developed the value of information (VoI) metric to mitigate the overwhelming amount data available. In this report, ARL researchers use C3TRACE software to simulate a basic human intelligence reports analysis process and observe if the results support the hypothesis that the VoI metric improves the SA gained in time-limited scenario.</p>					
15. SUBJECT TERMS value of information, constructive simulation, situational awareness, C3TRACE, military intelligence					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT UU	18. NUMBER OF PAGES 20	19a. NAME OF RESPONSIBLE PERSON John T Richardson
a. REPORT Unclassified	b. ABSTRACT Unclassified	c. THIS PAGE Unclassified			19b. TELEPHONE NUMBER (Include area code) 410-278-4143

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1. Introduction

In June 2015 the US Army Training and Doctrine Command published *US Army Warfighter Challenges*.¹ The purpose of this document was to identify “enduring first-order problems, the solutions to which improve the combat effectiveness of the current and future force”.¹ The number one challenge identified was “how to develop and sustain a high degree of situational understanding while operating in complex environments against determined, adaptive enemy organizations”.¹ In military command and control operations, situational awareness (SA) is crucial to good decision-making. Defined in Army Field Manual 5-0, situational understanding is the product of applying analysis and judgment to “relevant information” to determine the relationships among the operational and mission variables to facilitate decision-making.²

One of the central challenges associated with developing good situational understanding originates with the synthesis of timely and accurate information from the vast amounts of gathered intelligence. A critical aspect of that synthesis is the determination of the relative importance of the information gathered, with that decision being a function of operational tempo as well as the reliability, content, and latency of the information. For the military commander and his/her staff, separating the important information from the routine has become a labor-intensive task and impetus for this research.

Toward that end, a fuzzy-logic-based model was developed that codifies how intelligence analysts perceive the value of information (VoI) under varying operational tempos, source reliability, information content, and latency.³ The VoI metric is built using a fuzzy associative memory approach and is intended to codify the subjective deliberations of subject matter experts (SMEs) into fuzzy association rules capable of approximating the SME process for determining VoI.^{4,5} Hanratty et al. detail the approaches for elicitation of expertise from intelligence analysts at the US Army Research Laboratory (ARL) and for the construction of fuzzy association rules in the prototype VoI metric.⁶

This report evaluates the impact of the VoI metric within a constructive simulation and human performance model known as Command, Control, and Communications – Techniques for Reliable Assessment of Concept Execution (C3TRACE). C3TRACE was developed by the ARL’s Human Research and Engineering Directorate to specifically study “information-driven” decision-making within command and control structures.⁶

The remainder of this report is organized as follows: The details of the experimental design, data, and model are given, followed by a section that describes the simulated results. Conclusions and future work are presented in the final section.

2. Experimental Design

The goal of this experiment is to determine if applying a value rating to human intelligence (HUMINT) reports and then analyzing reports in order of highest value first can increase the SA gained in a finite-time period. The first step in designing the experiment was to gain a deeper understanding of the HUMINT analysis process by conducting several interviews with an Army officer and intelligence analyst. These interviews were the basis of the basic model and parameters used to control the simulation. The researchers developed synthetic data sets for the simulation and executed several trials with the simulation to determine the effect of using the VoI metric.

2.1 Data

The data for this experiment consisted of simulated HUMINT reports. The simulated reports consisted of a VoI rating and a content rating. The VoI rating was an integer value in the range 10 to 0, where 10 is the most valuable. During the simulation, the VoI rating is used to control the order in which reports are consumed. The content rating is a nominal value that places the report in one of 5 categories: Very Good, Good, Average, Bad, and Very Bad. The content rating determines several factors during the simulation, specifically the length of time to analyze the report, the amount of SA gained from this analysis, and whether or not the analysis precipitates further research.

Two data sets were generated for this experiment. Each consisted of 110 simulated reports (VoI and content rating) in a comma-separated value file. In this file the nominal content rating values were mapped to consecutive increasing integers, starting with Very Good = 1. The first data set used a uniform distribution of VoI values (Table 1). In this data set there are 10 reports for each VoI value. Furthermore, the content rating of each report is assigned in a method that creates a linear relationship between VoI rating and SA gained from analyzing the report.

Table 1 Uniform data set

VoI	Very Good	Good	Average	Bad	Very Bad
10	10	0	0	0	0
9	6	4	0	0	0
8	2	8	0	0	0
7	0	8	2	0	0
6	0	4	6	0	0
5	0	0	10	0	0
4	0	0	6	4	0
3	0	0	2	8	0
2	0	0	0	8	2
1	0	0	0	4	6
0	0	0	0	0	10

In this linear relationship, the SA gained by analyzing a report decreases with each decrement in VoI value (Fig 1). To calculate this relationship, the content rating values were each assigned an SA value (Table 2). In this simulation it is assumed that reading a report with a VoI value of 10 gains the analyst the maximum SA. Thus, all 10 reports with a VoI value of 10 were given a content rating of Very Good. Using the assigned SA values, the average SA gained from reading a report with VoI value of 10 was used as the starting point for generating the linear relationship. A decrease of 10% was chosen for each decrement in VoI value. Finally, a combination of content ratings that produced the desired average SA gained was selected for each VoI value.

**Uniform Dataset: Situational Awareness Gained
versus Vol Rating**

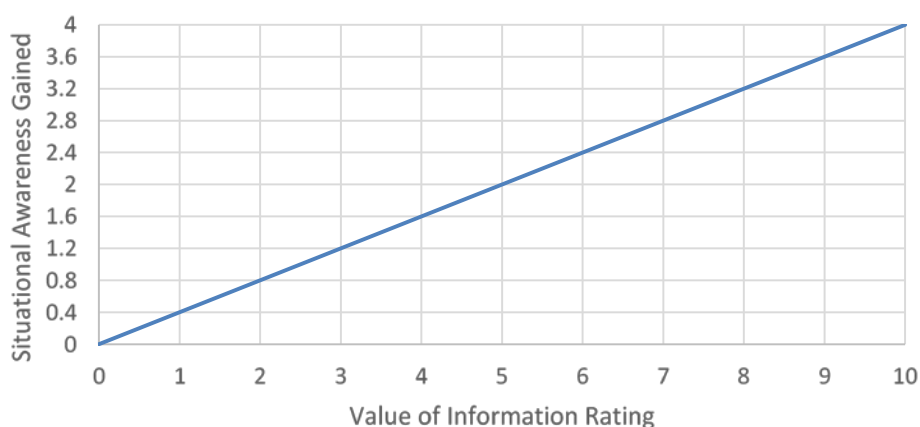


Fig. 1 Relationship between VoI and SA in the uniform data set

Table 2 Situational awareness gained based on content rating of report analyzed

Content rating	SA	Further investigation additional SA	Time factor (s)	Chance to investigate further (%)
Very Good	4	2	150	50
Good	3	2	150	40
Average	2	2	150	25
Bad	1	2	150	15
Very Bad	0	2	0	10

The second data set used a normal distribution of VoI values (Table 3). In this data set the amount of reports for each VoI value was determined by a normal distribution with a mean of 5 and encompassing the entire VoI scale within 3 standard deviations (Fig. 2). In addition, the content rating of each report is assigned in the previous linear relationship method, although it was not possible to achieve an exact fit due to the constraint of the SA values (Fig. 3).

Table 3 Normal data set

VoI	Very Good	Good	Average	Bad	Very Bad
10	1	0	0	0	0
9	1	0	0	0	0
8	1	4	0	0	0
7	0	10	3	0	0
6	0	9	13	0	0
5	0	0	26	0	0
4	0	0	13	9	0
3	0	0	3	10	0
2	0	0	0	4	1
1	0	0	0	0	1
0	0	0	0	0	1

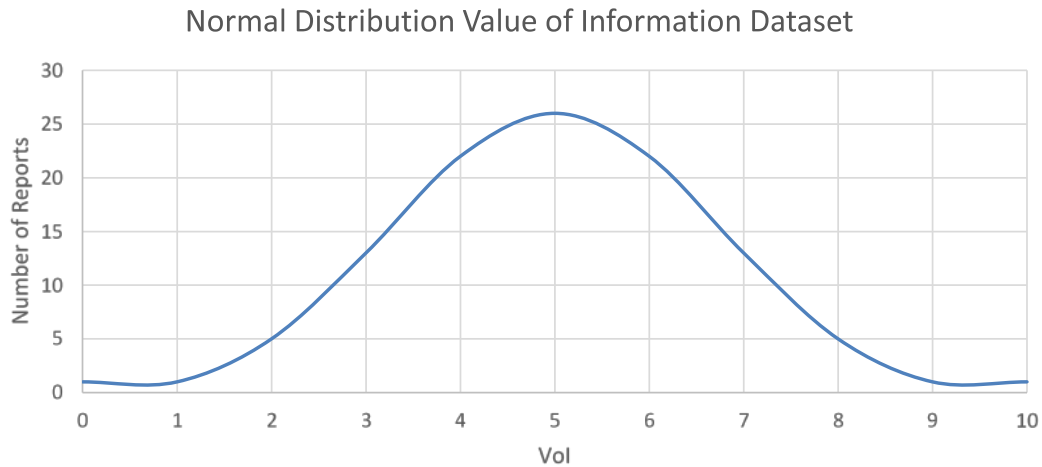


Fig. 2 Normal distribution used for VoI data set

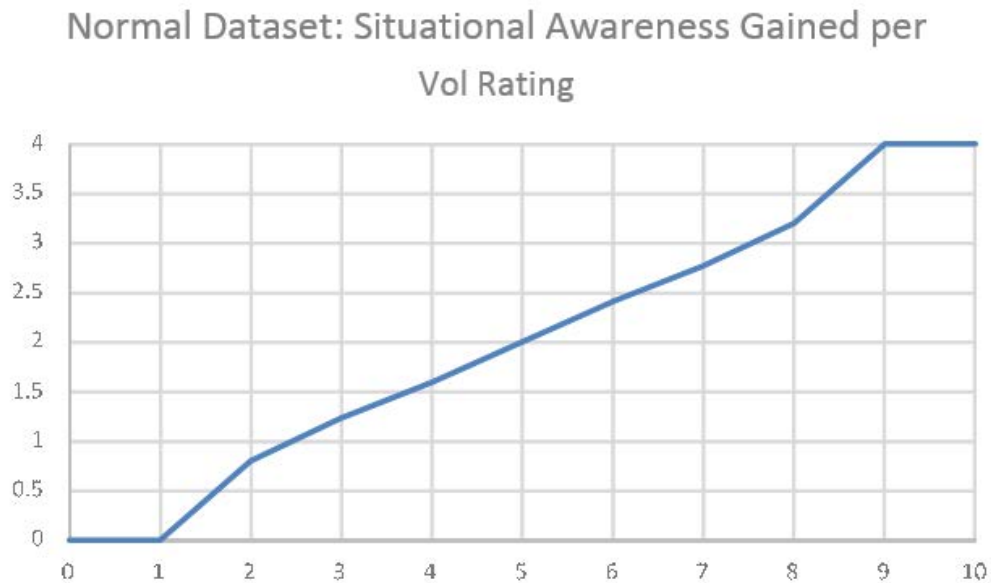


Fig. 3 Relationship between VoI and SA in the normal data set

The reason for the 2 data sets is to examine the effect of the data landscape on the utility of the VoI metric. The uniform distribution data set will allow study of the effect of the VoI metric on the SA gained from analyzing reports when the quality (content rating) of the reports is spread uniformly from Very Good to Very Bad. In contrast, the normal distribution data will allow a study of these effects when the majority of reports consist of a narrow range of VoI values.

2.2 Model

The model used in this experiment is created and exercised using the C3TRACE software (Fig. 4). As stated previously, the model is the product of several interviews with a US Army officer with war zone HUMINT analysis experience. The purpose of the model is to simulate the basic steps of HUMINT analysis. Using anecdotal knowledge derived from the SME it is possible to assign parameters to the steps to control the consumption of HUMINT reports and the SA gained. The overall scenario simulates a 12-h day of a HUMINT analysis. The analyst is tasked to review new HUMINT reports and present mission-relevant findings to the commander by the end of the day. The preparation and delivery of the presentation requires 2 h, thus the analyst only has 10 h to research the reports. The model combined with the simulated report data creates the experimental system. The experiment will answer if the VoI metric can increase the SA (the product of researching a report in this model) gained by the analyst during the 10-h period of time in this simulation. The C3TRACE reporting features are used to record the amount of reports analyzed, further investigations required, and the total amount of situational awareness gained.

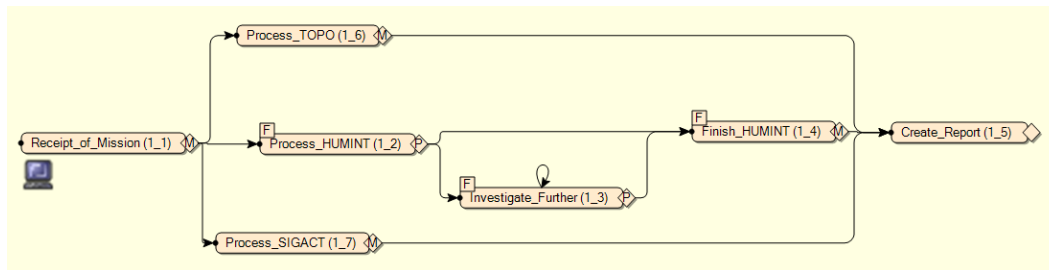


Fig. 4 C3TRACE workflow

The model is not intended to be an exhaustive representation of the complex task of HUMINT analysis. It is a basic process enhanced with anecdotal parameters. The purpose was to create a simulation able to deliver a quantitative first look at the impact of the VoI metric on SA gained. If the results precipitate additional research, the complexity of the model may be revisited.

2.2.1 Timekeeping

During the simulation C3TRACE increments the elapsed time as each report is analyzed. This is an important task because the scenario allows for only 10 h of analysis time. Multiple timing factors were used in the following formula to calculate the time elapsed as a result of analyzing a report:

Report Analysis Time = Analysis Baseline Time Factor

+ Report Time Factor

+ Further Investigation Time Factor * Number of Further Investigations

+Time between Reports

Several of the factors are constants in this experiment, derived from the anecdotal experience of the SME. The Analysis Baseline Time Factor is always 60 s, the Further Investigation Time Factor is always 600 s, and the Time between Reports is 60 s. The Report Time Factor and Number of Further Investigations are determined by the simulated content rating of the report (Table 2).

2.2.2 Situational Awareness Gained

Similar to timekeeping, the SA gained in the simulation is tracked by C3TRACE. Each time a report is completely processed or a further investigation occurs, a constant value (Table 2) is added to the total SA gained in the simulation. In this model, further investigation is considered a deeper exploration of the information in the original report, requiring additional research and analysis. This is a time-consuming process as the Further Investigation Time Factor demonstrates. Furthermore, the result of the further investigation may vary, but in this simulation it is set equivalent to the SA gained from analyzing an average report. The SA gained will be used to evaluate the performance of a given simulation.

2.2.3 C3TRACE Functions

The model is constructed of functions (Fig. 4) that represent basic steps in the analysis of a HUMINT report. Each function may increment the elapsed time and/or the SA gained given the content rating of report being processed. The functions are described in more detail in the following.

Receipt_of_Mission is the initial function in the model. It serves to maintain a FIFO (first in, first out) queue of HUMINT reports. During interviews it was discovered that the analyst preferred to completely process a report before moving on to the next report. Thus, this function will not begin processing a new report until the current report has processed all the way through the model. Furthermore, new reports will only begin processing if the simulation time is below the deadline threshold, which in our experiment is 10 h. If a report meets these requirements it is passed to the Process_HUMINT function.

Process_HUMINT is the function in the model that simulates analyzing a report. In this function the SA is incremented, and the time spent analyzing the report is calculated (time-elapsed formula). When this function has completed its task, the model has the option of 2 paths. It can either advance to Investigate_Further or Finish_HUMINT. The chance to Investigate_Further is given in Table 2 and is dependent on the content rating of the report. If the report does not advance to Investigate_Further, it goes to Finish_HUMINT by default. C3TRACE uses a random seed on each run of the model for use in all chance-based calculations. Hence, the path taken will be variable between runs.

Investigate_Further is the function in the model that simulates an analyst performing additional research into a report. In this function the SA is incremented and the time spent analyzing the report is calculated. Each execution of this function increments the elapsed time and the SA gained by constant values. They are set as constant in this function to avoid adding recursive complexity by simulating in detail the information discovered during further investigation. When this function has completed its task, the model has the option of 2 paths, just like the Process_HUMINT function. It can either return to Investigate_Further or advance to Finish_HUMINT. The chance to Investigate_Further is again given in Table 2 and is dependent on the content rating of the report. If the report does not advance to Investigate_Further, it goes to Finish_HUMINT by default. The recursive execution of Investigate_Further may only occur 3 times before the function is forced to take the default path to Finish_HUMINT.

Finish_HUMINT is the function where a report is considered processed. If the total time elapsed in the simulation is over the 10-h deadline, the model continues to Create_Report. Otherwise, Receipt_of_Mission is unlocked to begin processing the next report in the queue.

Create_Report is the last function in the model. When the elapsed time processing reports is greater than 10 h, this function is executed. The function increments the elapsed time by 2 h to simulate the time spent preparing and presenting the analysis to the commander. Thus, the total time spent in the model is 12 h. After the function terminates, the total SA gained, reports processed, and further investigations performed are recorded.

2.3 Experiment

The goal of the simulation is to record the value of the SA gained from analyzing as many reports as possible within a 10-h time limit of the simulation. The order that the reports are analyzed is determined by the VoI value. At the beginning of a trial, the report file is ingested by C3TRACE, and the order of the individual reports is randomized by performing a Fisher-Yates Shuffle. Then a portion of the reports from the beginning of the shuffled list is sorted by VoI value to place the highest-value reports in a position to be analyzed first. The portion of the reports that was sorted is called the “queue”, and its size was changed between trials. After the sorted reports in the queue are analyzed, the remaining reports are analyzed in the random order in which they were shuffled at the beginning of the simulation. For each data set there were 11 trials. The first trial had a queue of zero, meaning no sorting of the reports was performed. This is the worst-case scenario, as the reports are ingested in a random manner according to the initial shuffle. At the beginning of each successive trial, the queue size is increased by 10, culminating in the 11th trial, where the queue size is 110, which is the size of the entire data set. This last trial is the best-case scenario since all the reports are sorted according to their VoI value. Furthermore, during each trial, the simulation is run 110 times. During each run the total SA gained and the number of reports analyzed is recorded.

3. Results

The experimental results were collected using the C3TRACE default reporting and macro features to tally the SA gained and reports analyzed. The results were plotted to show the relationship between the average SA gained and the average queue deficit.

The queue deficit is the difference between the queue size used for the trial and the average number of reports analyzed across all the runs in that trial. This plot shows that for the Uniform Data Set, the SA gained does not improve until the queue deficit disappears and becomes a surplus (Fig. 5). In other words, the SA begins to improve once more reports are sorted than the simulation is able to analyze. On the contrary, the plot showing the results using the Normal Data Set reveals that the SA gained never improves regardless of queue deficit (Fig. 6).

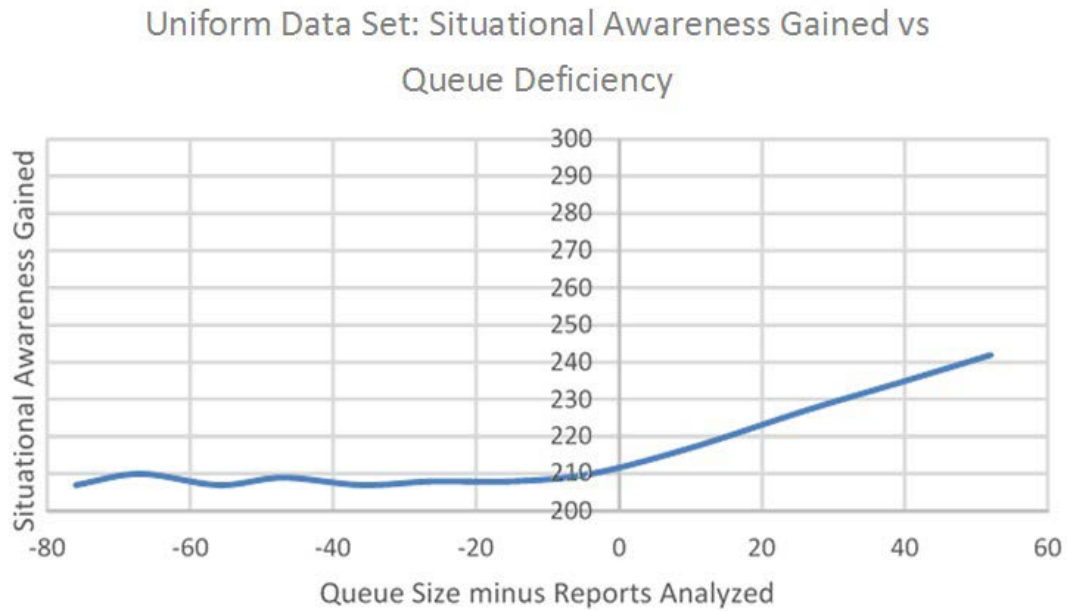


Fig. 5 Uniform data set results

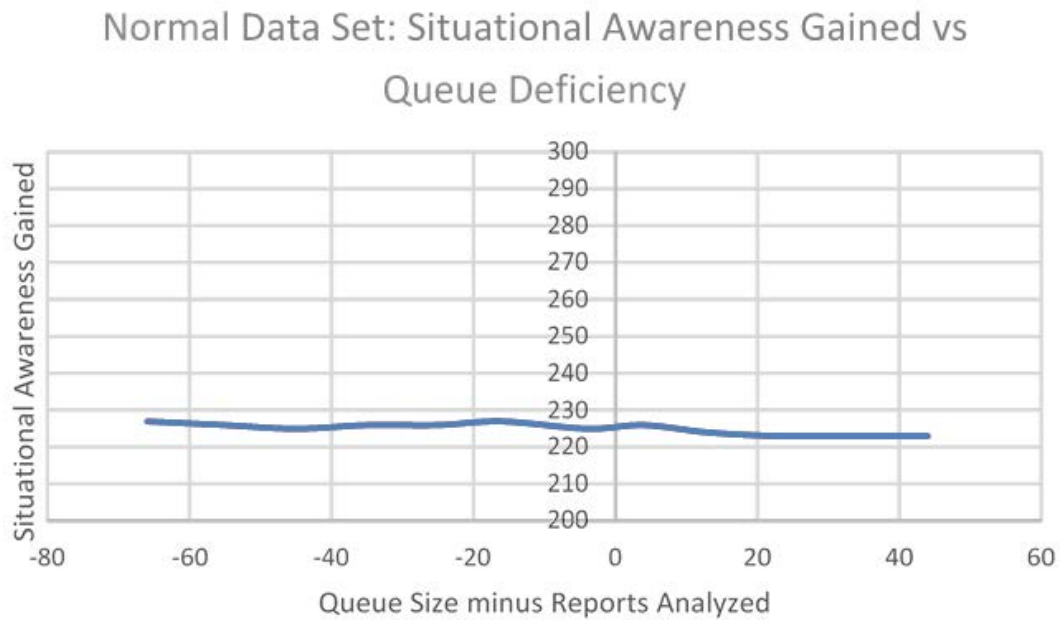


Fig. 6 Normal data set results

These results indicate that the data environment has a role in determining if the VoI metric has an effect on SA gained in this simulation. This experiment looked at 2 possible data distributions, uniform and normal. In the trials using the uniform data set, the VoI metric did improve the SA gained once the queue size was greater than the number of reports analyzed. If the queue size is smaller than the amount of

reports analyzed, all the reports in the queue would have been read anyway, and sorting based on the VoI metric gains nothing. To illustrate, if the queue size is 10, the first 10 reports in the shuffled list were sorted by VoI value and the remaining 100 were left in their shuffled order. If the simulation analyzes more than 10 reports, the sorting was meaningless because all 10 reports were read in the end. If the simulation only reads 5 reports, the VoI metric improves SA gained because the best 5 reports are from the sorted portion of the list.

On the contrary, the results show that the SA gained during trials with the normal data set do not change under any circumstance in the simulation. Due to the normal distribution, approximately 68% of the data is within one standard deviation of the mean VoI value (5 in this experiment). Since the majority of the reports are close to the same VoI value, there does not appear to be enough variation to make sorting the reports by VoI value meaningful.

4. Conclusion

The potential to assist an analyst in digesting the most valuable intelligence first is an important component in shortening the time from data to decisions. In this experiment, the simulation results showed that the benefit of the proposed VoI metric has a strong dependence on the nature of the data to which it is applied. If you consider the experimental data sets to be the endpoints of a spectrum of scenarios (spread out versus clustered together), the results show that the impact of the VoI metric is greatest in the scenario where the value of the reports are evenly distributed. It is ineffective when the value of the reports are clustered closely together. Further research is necessary to gauge the impact of VoI on data sets that exist between the endpoints of the spectrum and to attempt to discern how real-world data behave.

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List of Symbols, Abbreviations, and Acronyms

ARL	US Army Research Laboratory
C3TRACE	Command, Control, and Communications – Techniques for Reliable Assessment of Concept Execution
HUMINT	human intelligence
SA	situational awareness
SME	subject matter expert
VoI	value of information

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